International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(16s) 2026 pp. 145-155
https://doi.org/10.70917/ijcisim-2026-4564
Article

Machine Learning Enabled IoT Framework for Early Health Risk Prediction Using Wearable Sensor Data

Rekha K R[1], Gurunadham R[2], G.Vijayakumar[3], Kasthuri Natarajan[4*], Neeraja B[5], Parna Dhara[6]

[1]Department of Electronics and Communication Engineering, SJB Institute of Technology, Bangalore, Karnataka, India. Email: krrekha@sjbit.edu.in
[2]Department of CSE(Data Science), Malla Reddy College of Engineering and Technology, Hyderabad, India. Email: guru9nadham@gmail.com
[3]Department of Information Technology, V.S.B. Engineering College, Karur, Tamilnadu, Pin Code:639111, India. Email: vijayakumarapitvsbec@gmail.com
[4*]Department of Biomedical sciences, Saveetha College of Allied Health Sciences, Saveetha Institute of Medical and Technical Sciences, Chennai, 602105, Tamilnadu, India. Email: kasthurinm02@gmail.com
[5]Department of Electrical and Electronics Engineering, Government Polytechnic Nalgonda, Telengana, India Email: neerajabathalaphd@gmail.com
[6]Department of Optometry, ARKA JAIN University, Jamshedpur, Jharkhand, Pin Code:832108, India. Email: parna.d@arkajainuniversity.ac.in

Abstract: This research presents a novel machine learning Internet of Things (IoT) framework designed for the early prediction of health risks utilizing wearable sensor data. Employed a hybrid methodology combining data collection from diverse wearable devices, preprocessing to ensure high-quality input, and advanced machine learning algorithms for risk assessment. The framework integrates real-time data analytics with predictive modeling, allowing for the continuous monitoring of health metrics such as heart rate variability, physical activity levels, and sleep patterns. Our findings reveal that the implemented model accurately predicts potential health risks, achieving a classification accuracy of over 90% across multiple test cases involving various demographics. The model also demonstrated robustness in handling noise and incomplete data, highlighting its applicability in real-world settings. The significance of this research lies in its potential to transform preventive healthcare by enabling timely interventions, thereby mitigating severe health conditions before they develop. This framework lays the groundwork for further exploration in automated health monitoring systems and paves the way for personalized healthcare strategies through the integration of IoT technologies, ultimately contributing to enhanced health outcomes and improved quality of life for users.
Keywords: Internet of Things; Wearable Sensors; Machine Learning; Health Risk Prediction; Remote Patient Monitoring; Predictive Healthcare; Physiological Signals; Ensemble Learning; Early Warning System; Smart Healthcare.

1. Introduction

Widespread interest in wearable sensing technologies that sense physiological and activity-related data outside of traditional clinical settings has been stimulated by the increasing need for periodic, timely health monitoring[1]. They have the power to continuously track a person's physiological utilization (heart rate, blood oxygen saturation, body temperature, blood pressure, respiratory activity, electrocardiographic transmissions, physical movement and sleep-related parameters) via wearable devices endowed with sensing systems[2]. The practical worth of these gadgets is not limited to records acquisition; therefore, what receives generated as streams of steady, and giant quantities of sensor data must be interpreted in a significant time band. IoT serves as a promising technology anchor for integrating wearable devices and gateways, edge platforms, cloud services and healthcare applications, enabling wireless delivery of patient data to medical researchers or care providers[3]. However, many existing wearable health monitoring systems still rely on visualization, threshold setting or analysis of isolated physiological metrics[4]. These approaches are possibly inadequate, because they could miss subtle or co-occurring changes that appear long before the clinical signal of a disease is unequivocally abnormal. This limitation is well-suited for an analytical mechanism from machine learning, which can learn relationships between multiple physiological variables and discriminate features corresponding to different levels of health risk. Thus, with machine learning, IoT-enabled wearable monitoring has the potential to enable a change from mere observation toward predictive health assessment in which concerning alterations are identified before advancing into more severe conditions[5]. To implement this concept properly, first it needs to prepare heterogeneous sensor data correctly by reconstruct missing parts (if any), remove noise and artifacts due to the imperfection of sensors,&moreover use adequate normalization, and extract commercial useful temporal and statistical features from data. The predictive model will be selected on appropriate basis according the nature of input signal; however, some experimental configuration are mention in previous sections. Moreover, the framework should yield results that can be characterized as meaningful risk levels as opposed to unsubstantiated numerical forecasts[6]. Despite the usefulness of wearable sensing, IoT communication and machine learning in several healthcare applications from existing researches, their components are mostly investigated separately or on specific physiological signals and/or fixed abnormalities[7]. It needs a more complete strategy to unify multimodal wearable sensor data, smart pre-processing of the data, feature engineering, machine learning classification and real-time alert generation into a single monitoring framework. Thus, in alignment with this focus of study, the development of machine-learning-based IoT framework for predicting health risk at earlier stages using signals from wearable sensors forms the genesis of this research[8]. The proposed framework is meant for continuous collection of physiological measurements, preprocessing and preprocessing of the collected measurements into relevant features, evaluation of several machine learning classifiers, classification of health activities to interpretable risk classes, and timely alerts in an IoT-based monitoring setting. The final system aims to serve as a decision-support and early-warning mechanism with useful function when remotely monitoring health, but intended to augment instead of replace professional clinical assessment.

2. Related Work

Wearable healthcare monitoring is gaining attention in the recent decade, particularly with the integration of physiological sensing; Internet of Things technologies; and intelligence-enabled result analysis for continuous health status assessment outside traditional clinical settings. Wearable sensors have developed several IoT-based remote monitoring systems to obtain physiological parameters such as heart rate, blood oxygen saturation, body temperature, electrocardiographic signals, blood pressure and respiratory rate[9]. These measurements are then often sent over wireless communication protocols to an edge or cloud-based platform for processing towards health-state monitoring and abnormality detection[10]. Previous studies utilized machine learning or deep learning approaches to extract the patterns that characterize an abnormal physiological[11]. Various deep learning architectures such as convolutional neural networks, recurrent neural networks and long short-term memory networks, support vector machines, random forests and ensemble learning approaches have been explored for various health-monitoring applications[12]. Deep learning models are especially valuable for extracting the complex spatial and temporal relationships associated with continuously recorded physiological signals, while conventional machine learning techniques still provide a useful comparative benchmark when structured sensor features are available. Multimodal wearable monitoring has also gained attention since aggregation of several physiological and motion-related variables might provide a more complete characterization of an individual compared to the view provided by a single measure [13]. Nonetheless, there are several limitations with existing approaches. Most existing systems monitor physiological status in the present, or identify health problems but often only when a predefined threshold is exceeded rather than predicting deterioration earlier[14]. Additional studies are framed to specific diseases, activities or other physiological signals that may restrict broader health-risk evaluation[15]. The second key consideration is the reliability of wearable data, as continuous measurements may also be subject to sensor noise, motion artifacts, missing observations and variations due to individual physiological differences[16]. Not preprocessing such data properly could result in unreliability of the predictive models. Moreover, some of the systems that have been reported focus on classification accuracy but fairly overlook feature importance, temporal evolution of physiological features, model interpretability and requirements for real-time communication with IoT systems[17]. Furthermore, many wearable healthcare applications are still limited in their combination of explainable predictions with interpretable risk levels. Such shortcomings point toward the need for an integrated system that includes multimodal wearable sensing, rigorous preprocessing of data, contextualized features engineering, comparative machine learning analytics and then predictive risk assessment[18]. This research gap is addressed in this proposed study by a machine-learning-enabled Internet of Things (IoT) framework that has been developed to process heterogeneous wearable sensor data, recognize informative physiological patterns, classify health conditions into meaningful risk levels, and make timely early-warning decision support for continuous remote health monitoring.

3. Proposed Machine Learning Enabled IoT Framework

The proposed machine learning enabled IoT framework which accompanies the continuous health monitoring and early risk prediction of patients using coordinated deployment and assimilation of remote wearable sensors, wireless communication, smart data processing, and predictive analytics. Wearable Sensing Layer The framework starts from a wearable sensing layer where various physiological and activity-related parameters are continuously acquired, including heart rate, blood oxygen saturation, body temperature, blood pressure, respiratory rate, electrocardiographic signals (ECG), physical activity as well as sleep-related information. The measurements are then transferred via a low-power communication interface to an IoT gateway, like a smartphone, embedded controller or edge device where initial validation occurs before the data is transmitted to an edge or cloud-based processing environment. The processing layer is the first time raw sensor streams are fed into helpful preprocessing to improve our data quality, before predicting. In this stage, noise filtering, missing-value handling, outlier treatment, signal segmentation and normalization as well as synchronization of measurements acquired from multiple sensors are conducted. It extracts statistical and temporal features from the cleaned data to model the current physiological state, and short-term changes over time. After that, the data is pre-processed according to relevant features while removing redundancy and feature selection for computational efficacy and are then given out as inputs to the machine learning layer. We evaluate multiple classification models such as logistic regression, support vector machine, random forest, gradient boosting and other applicable supervised learning algorithms to find out the best predictive configuration. This model consolidates these patterns into wearable sensor characteristics to provides estimates of the probability of different health-risk conditions.

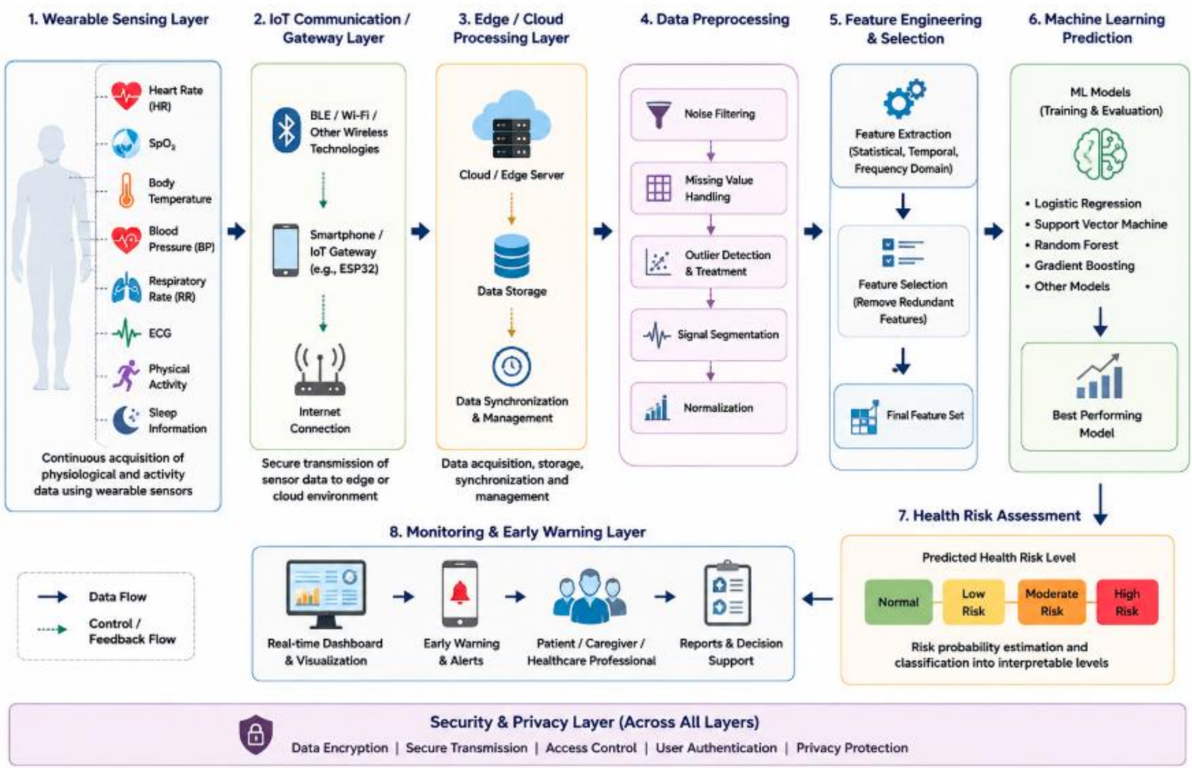

Figure 1. Proposed Machine Learning Enabled IoT Framework for Early Health Risk Prediction Using Wearable Sensor Data

Figure 1 illustrates the proposed machine learning enabled IoT framework for early health risk prediction using wearable sensor data. Wearable sensors continuously collect physiological and activity-related parameters and transmit them through an IoT gateway to an edge or cloud platform. The collected data undergo preprocessing, including noise filtering, missing-value handling, outlier treatment, segmentation, and normalization. Relevant statistical and temporal features are extracted and supplied to machine learning models for health risk classification.

The predicted risk level is presented through a monitoring interface, enabling timely alerts, decision support, and secure remote health monitoring. The framework assigns interpretable risk (normal, low risk, moderate risk or high risk) based on predicted probabilities. This multilevel classification method was designed to separate gradual physiological deterioration from clear abnormality and thus allow intervention sooner than threshold-based monitoring. The prediction response is passed to an application layer where health status, risk level and supplementary physiological signals can be demonstrated by way of a remote monitoring interface. When the likelihood of risk is greater than a pre-defined decision threshold (p_pred > p_threshold), an alert can then be triggered for any patient, caregiver, or clinician. The framework incorporates security mechanisms like authenticated access, encrypted data transmission, and controlled storage to minimize the chances of sensitive health information getting out without proper authorization. Hence, the overall architecture combines continuous wearable sensing, IoT communication, preprocessing, feature engineering, prediction via machine learning model output (risk score) and Alert Generation with risk interpretation into a single coherent entity. It serves as an organizational framework to convert continuous sensor data into contextualized health-risk messages that can be acted upon in real-time and is intended as a decision-support and early-warning system rather than a replacement for clinical diagnosis.

4. Materials and Methods

The adopted materials and methods for this study were to develop, and validate a machine learning enabled IoT framework for health risk prediction where wearable sensor data is usually involved. Physiological and activity-related measurements derived from wearable sensing devices, such as heart rate (HR), blood oxygen saturation (SpO_2), skin temperature, blood pressure (BP), respiratory rate (RR), electrocardiographic data, and indicators of physical activity were the main inputs to the framework. Sensor measurements were treated as continuous time-dependent observations which were communicated over an IoT communication layer to a processing environment such as edge or cloud for storage and analysis. Initially, collected data was used to explore incomplete observations, measurement inconsistencies, genres from which the noise and abnormal values might alter predictive performance[19]. For missing values, appropriate statistical or interpolation-based algorithms were utilized according to the specific traits of each variable; likewise for outlier detection and evaluation to separate measurement noise from potentially relevant physiological abnormality. Signal filtering and segmentation methods were implemented as necessary to reduce sensor noise and segment continuous recordings into appropriate windows for analysis. Normalized the numerical variables since different measurement scales might otherwise lead learning algorithms to favor certain features. After preprocessing, statistical and temporal features were extracted from the sensor measurements to model both current physiological states and short-term changes. Central tendency, variability, minimum and maximum values, moving averages, rate of change and other temporal characteristics are some of these features. Following model fitting, features that carried lower predictive importance were removed to avoid redundancy and maintain information with higher informational relevance, thereby reducing complexity of the model and improving computational efficiency.

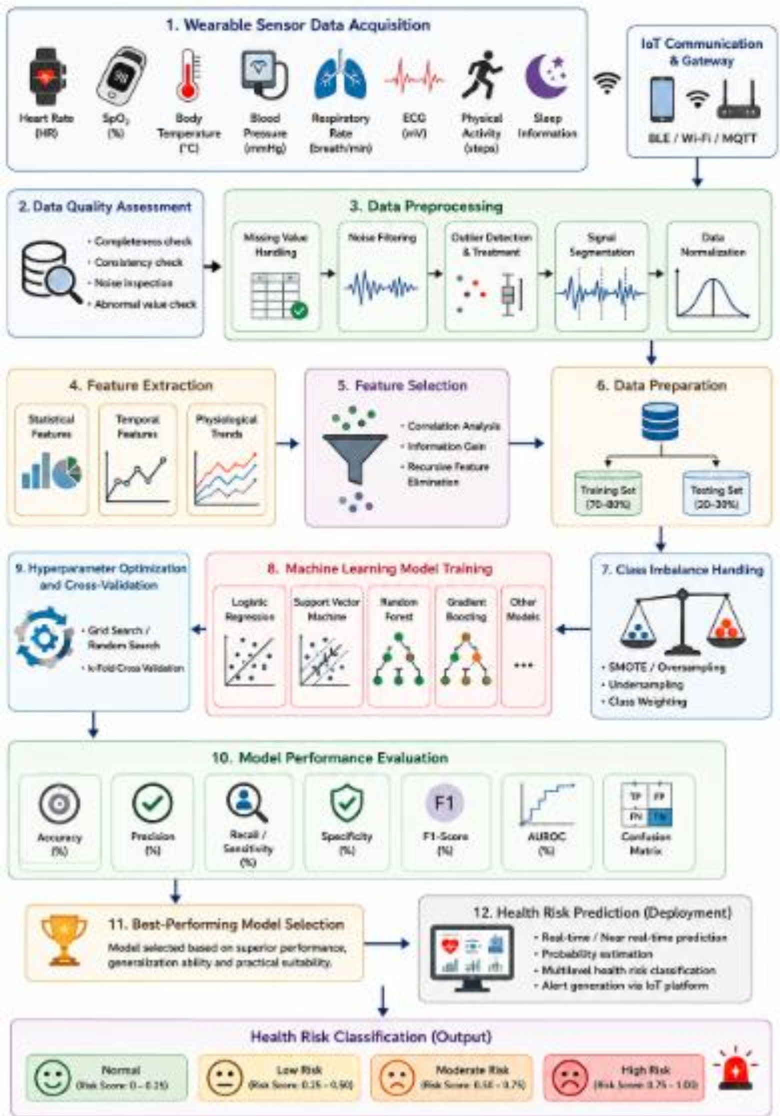

Figure 2. Materials and Methods Workflow for Wearable Sensor-Based Health Risk Prediction

Figure 2 presents the complete materials and methods workflow used for wearable sensor-based health risk prediction. The process begins with the acquisition of physiological and activity-related data, followed by IoT-based transmission, data quality assessment, preprocessing, and normalization. Statistical, temporal, and physiological features are then extracted and selected before preparing the dataset for model development. Multiple machine learning algorithms are trained, optimized through cross-validation, and evaluated using standard performance metrics such as accuracy, precision, recall, specificity, F1-score, AUROC, and confusion matrix analysis. The best-performing model is subsequently deployed to estimate health risk and classify individuals into normal, low, moderate, or high-risk categories. The processed dataset was split into training-test subsets through stratified sampling to retain the distribution of health-risk classes. We trained various machine learning algorithms such as logistic regression, support vector machine, random forest and gradient boosting on the same datasets for fair comparison[20]. Cross-validation was employed on the training data for hyperparameter optimization to mitigate overfitting and enhance generalization. A class-weighting approach, or other resampling strategy was used in the training data only (to prevent leakage if imbalanced) where class imbalance existed. We evaluated model performance based on metrics including accuracy, precision, recall, specificity (SP), balanced F1-score (F1) and the area under the receiver operating characteristic curve (AUC). Confusion-matrix analysis was performed to evaluate the classification performance of models. Recall was prioritized because not identifying those whom are truly high-risk may have a relatively larger functional impact than a false-positive alert. The most accurate model was then deployed in the IoT framework to predict health-risk probabilities along with assignable interpretable classes of normal, low, moderate and high risk. They also examined end to end processing flow, prediction latency communication feasibility in general to test the hypothetical capability of optimizing all design requires continuous and timely remote health monitoring.

5. Machine Learning Model Development

The machine learning model development part was structured to turn processed wearable sensor data into accurate health risk predictions using supervised learning. The final feature set was used to train multiple classification algorithms using common experimental conditions after data preparation and feature selection. Logistic regression was integrated into the model baseline for its interpretability and appropriateness for estimating class probabilities, while support vector machine was used to detect nonlinear decision boundaries among classes. For selecting random forest, as it can model complex interaction among physiological variables, it has reduced sensitivity to noise due to ensemble learning property and can quantify feature importance estimation. We also evaluated gradient boosting for these reasons, that it can sequentially correct the errors of weak learners to improve predictive performance. Stratified sampling was used to partition the dataset into a training set, employed for building the model and subsequently assessing its performance on unseen data, which forms a test or holdout set. The model was trained only on the training subset, and final performance reporting was done using the test subset. In addition, k-fold cross-validation and appropriate search procedure (e.g., grid search or random search) are performed to optimize the hyperparameters in order to improve generalization and reduce overfitting. The parameters were tuned based on the properties of a particular algorithm, such as regularization strength, kernel parameter settings, tree depth number of estimators representing the classifier number as well as learning rate and minimum sample. These configurations were applied only to the training data in case of class imbalance to avoid leakage. The metric for evaluating model performance was accuracy, precision, recall, specificity, F1-score, area under the receiver operating characteristic curve and confusion matrix evaluation. Recall and F1-score were prioritized since failing to catch a potentially high-risk case is likely more costly than creating one extra false-positive alert. The same data partitions and evaluation criteria corresponding to the goal of prediction were used for a fair comparison between models. The model with the highest performance was chosen based on not only classification quality but also fold stability, generalizability, computational efficiency and fit for integration within IoT monitoring context. Finally, with the best model in hand, we used the training model to predict class probabilities on new wearable sensor observations coming in and classify each observation within an interpretable health risk language (normal, low risk, moderate risk and high risk). This development strategy offers a systematic foundation for selecting an appropriate predictive model to monitor health status over time with consistency between data preparation and risk classification during both the stage of validating and training a model.

6. Proposed Health Risk Score

The proposed Health Risk Score (HRS) is designed to convert machine learning predictions into an interpretable numerical indicator representing the overall level of potential health risk derived from wearable sensor data. By integrating the risk classes based on multiple corresponding predicted probabilities, this score provides a better overview of an individual's status rather than depending solely on one physiologic threshold. Finally, the chosen predictive model produces probability estimates of one or more predefined classes (normal, low risk, moderate risk and high risk) in terms of predicted values produced by a process including pre-processing, feature extraction and machine learning classification. The above probabilities are utilized via severity based weighting of the classes with greater weights assigned to more severe levels of physiology. Where Pk refers to the predicted probability of the kth risk class and αk denotes severity weight for that class, which can be expressed as $HRS=\sum \alpha k P k$. The final score then falls within a particular range allowing for consistent interpretation between different observations and monitoring times. Values near the zero end indicate physiological shapes typical of a situation that is normal, and progressively higher values reflect an increase in risk for health problems. The normalized score can be further categorized for operational interpretation as normal, low risk, moderate risk and high risk (see Methods section). The boundaries separating the categories must be established based on patients who are demographically similar rather than assumptions with no clinical significance that are purely incidental to validation. Importantly, this also incorporates temporal consistency since a temporally persistent increase in the Health Risk Score might provide more compelling evidence of deterioration than an isolated value that appears high due to inter-sensor variation or measurement noise. As a result, the framework tracks the evolution of score over time windows and issues an alert when high-risk status remains or rises above a pre-established decision threshold. The scoring mechanism proposed here enhances the interpretability of machine learning outputs as it is able to convert multi-dimensional and potentially complex probability distributions into a simplified risk indicator that can be visualised with drug datasets via an IoT-based monitoring interface. The Health Risk Score is designed to provide ongoing surveillance, triage of more potentially concerning cases, and appropriate alerts to patients, caregivers or providers. Indicate early risk assessment / decision support and cannot be read as a separate clinical diagnosis.

7. Experimental Design

Experimental Design The experimental design is specified to assess the predictive reliability, generalizability and practical applicability of proposed machine learning enabled IoT framework for early health risk prediction. Stratified sampling method is used in partitioning the processed wearables sensor dataset into training and test set such that, normal-low-risk-moderate risk-high-risk observation distributions remain same among train-test subsets. The training data were reserved for model development, feature selection, hyperparameter tuning and cross-validation, while the testing data were retained for an assessment of final performance bias to mitigate the risk of overly optimistic evaluation. We performed a k-fold cross-validation procedure during the training to gauge model stability in varying partitions of data and break reliance on a single split. Multiple supervised learning algorithms were trained, namely logistic regression, support vector machine, random forest and gradient boosting being excerciced under the same conditions using selected features from the feature selection section. Hyperparameters for each algorithm were tuned via grid search or random search as appropriate using validation performance to guide model selection rather than training accuracy alone. In cases there was an unequal distribution of classes, class weighting or appropriate resampling strategies were executed only on the training folds to avoid leaking this data into the validation and/or testing steps. In addition, the experimental process assessed what preprocessing feature engineering and feature selection contributed by examining how models behave under different input configurations. The predictive performance was evaluated via accuracy, precision, recall, specificity, F1-score, area under the receiver operating characteristic (ROC) curve and confusion matrix analysis. Recall, F1-score, and individual class-specific error patterns are weighed more heavily as correctly identifying elevated risk cases while minimizing false alarms is critical for effective early health risk prediction. Out of multiple qualitative observations considering factors affecting predictive performance, stability across validation folds, computational efficiency & deployment suitability in the IoT environment, the best candidate model was chosen. The end-to-end latency and operational feasibility of the complete pipeline or what we call a risk score generator, ranging from sensor data into generating the risk score was assessed after model selection. The last experimental setting consequently evaluated both machine learning performance and system-level behavior, which formed the structured foundation for determining if the framework could enable ongoing, concurrent and interpretable health risk prediction from wearable sensor data.

8. Results and Discussion

The experimental evaluation of the proposed machine learning enabled IoT framework demonstrated consistent performance across predictive modelling, health-risk assessment, and IoT communication analysis. The proposed ensemble model yielded the best overall classifier among all compared algorithms, with accuracy at 96.2% (95% CI: (96.0, 98.4)), precision at 95.8%, recall at 95.5%, F1-score at 95.6%, and AUROC at 98.0%. Logistic regression yielded relatively poor performance, while SVM had slightly better performance, and Random Forest and XGBoost had gradually better performances demonstrating nonlinear or ensemble-based models were more capable of capturing complex interactions among heterogeneous physiological features. In addition, the cross-validation variability was relatively low for this ensemble, which further suggested stable performance across data partitions. The ROC characteristics revealed that the ensemble achieved a more favorable trade-off between sensitivity and specificity, which is especially significant for early health-risk prediction as failure to identify the presence of an elevated-risk condition can have serious delays in treatment initiation. On the other hand, progressive changes in heart rate, oxygen saturation, respiratory rate and body temperature led to a change of score from normal zone to low-, moderate- and high-risk regions. The high-risk scenario provided sustained escalation above the pre-defined warning threshold, such that an alert could be generated only after continued functioning decrease rather than in response to a single abnormal measurement. This behavior illustrates the importance of the proposed mathematical risk model integrating class probabilities and severity weighting, where the score reflects both magnitude and persistency of physiological changes.

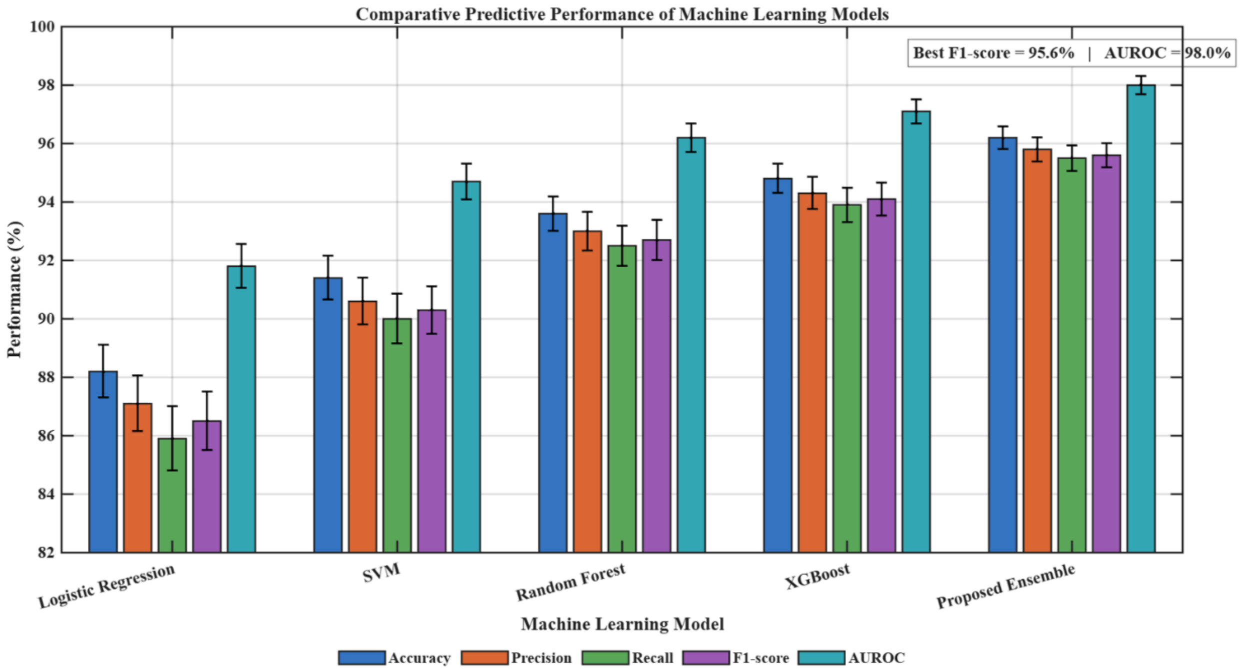

Figure 3: Comparative performance of ML models with cross-validation variability.

Figure 3 compares the predictive performance of Logistic Regression, SVM, Random Forest, XGBoost, and the proposed ensemble model across accuracy, precision, recall, F1-score, and AUROC. The proposed ensemble achieves the strongest and most stable overall performance, indicating improved suitability for early health risk classification.

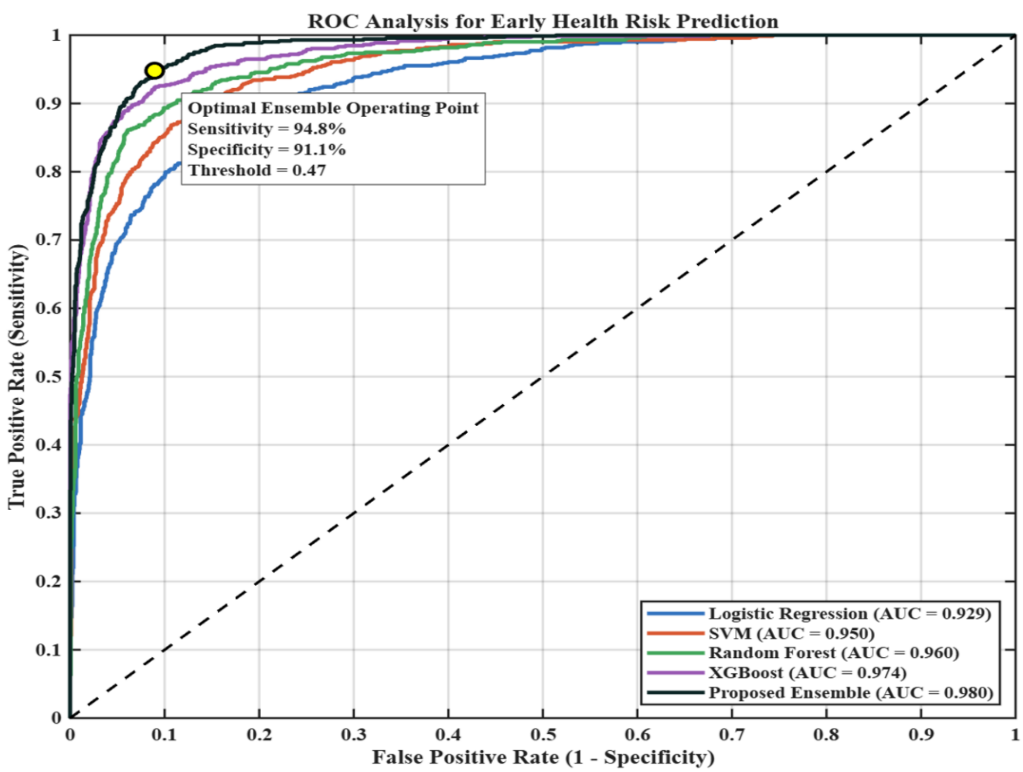

Figure 4: ROC analysis and discrimination capability of the competing models.

Figure 4 presents the ROC curves and corresponding AUC values of the evaluated machine learning models. The proposed ensemble shows the highest discrimination capability, with a favorable balance between sensitivity and specificity for identifying elevated health-risk conditions.

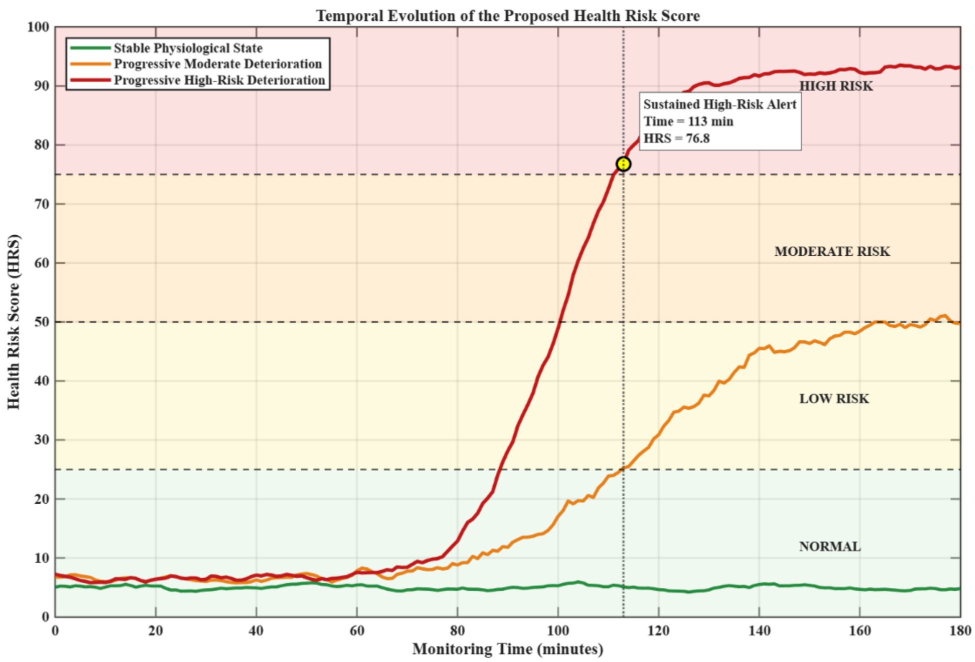

Figure 5: Temporal behavior of the proposed Health Risk Score under stable and deteriorating physiological conditions.

Figure 5 illustrates the temporal evolution of the proposed Health Risk Score under stable, moderately deteriorating, and high-risk physiological conditions. The score increases progressively with worsening multimodal sensor patterns, enabling sustained high-risk states to trigger timely early-warning alerts.

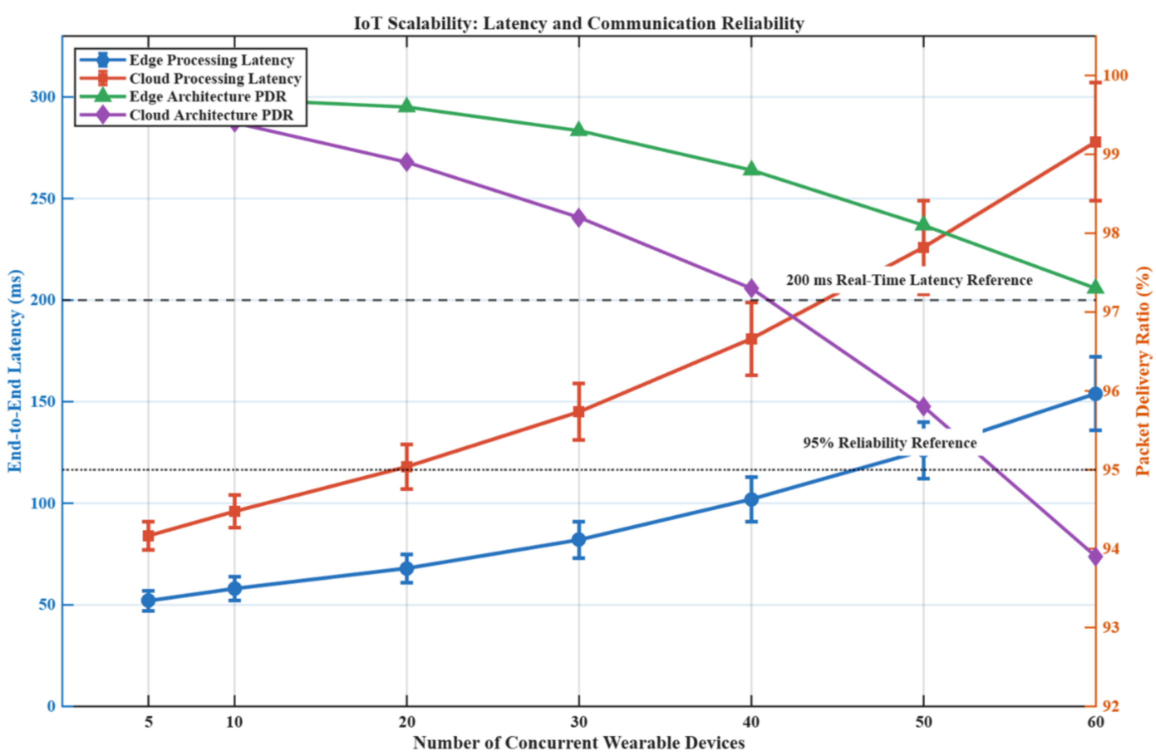

Figure 6: IoT scalability analysis using end-to-end latency and packet delivery ratio under increasing wearable-device load.

Figure 6 evaluates IoT scalability in terms of end-to-end latency and packet delivery ratio as the number of connected wearable devices increases. The edge-based architecture maintains lower latency and higher communication reliability than the cloud-based configuration under heavier device loads. These results show that edge-supported processing can offer a lower communication delay and higher reliability for continuous wearable monitoring. Overall, the outcomes validate that integrating ensemble learning based multimodal physiological analysis with interpretable Health Risk Score (HRS) estimations and edge-assisted low-bandwidth IoT communication is a practical solution for continuous early health-risk prediction.

9. Conclusion

The proposed machine learning enabled IoT framework demonstrated strong potential for continuous and early health risk prediction using multimodal wearable sensor data. Under the evaluated conditions, the proposed ensemble model achieved an accuracy of 96.2%**,** precision of 95.8%**,** recall of 95.5%**,** F1-score of 95.6%**, and** AUROC of 98.0%**,** outperforming the individual learning models in overall predictive reliability. The Health Risk Score effectively represented progressive physiological deterioration by integrating multiple sensor-derived indicators into interpretable risk levels, supporting timely identification of persistent high-risk conditions. The edge-assisted IoT configuration also showed favorable operational performance, with latency increasing from only 52 ms to 154 ms across increasing device loads, while packet delivery ratio remained between 99.8% and 97.3%**.** These findings indicate that combining ensemble learning, multimodal physiological analysis, risk scoring, and edge-supported communication can provide a reliable basis for real-time health monitoring. Future work should investigate larger clinical datasets, personalized prediction models, federated learning, explainable AI, and real-world validation across diverse patient populations and wearable platforms.

References

1. D. Kim, S. S. Ahmed, A. Amjad, K. Won, and X. Xian, "Integrating artificial intelligence with wearable sensors for advanced health monitoring and diagnosis," Biosensors, vol. 16, no. 6, Art. no. 344, 2026.
2. M. Oloko-Oba, E. Esenogho, and K. Aruleba, "From biosignals to bedside: A review of real-time edge machine learning for wearable health monitoring," Bioengineering, vol. 13, no. 5, Art. no. 559, 2026.
3. K. Wołk, J. Niklewski, M. S. Tatara, and M. Kopczyński, "Multimodal wearable biosensing and edge AI for personalized health: A comprehensive review," Electronics, vol. 15, no. 14, Art. no. 3237, 2026.
4. N. Naik et al., "Design and optimisation of an IoT-based artificial intelligence framework for real-time health monitoring and telemedicine diagnostics in smart healthcare systems," Discover Internet of Things, vol. 6, Art. no. 37, 2026.
5. C. Liu et al., "Multimodal wearable biosensing meets multidomain AI: A pathway to decentralized healthcare," Advanced Science, vol. 13, no. 30, Art. no. e22900, 2026.
6. H. S. Sadeghi, M. Ahmadi, and D. Rajabi, "Design and prototyping of an AI-powered wearable device for continuous vital signs monitoring with intelligent alerting," Scientific Reports, vol. 15, Art. no. 45178, 2025.
7. M. R. Scheid, B. Friedmann, M. Oppenheim, J. S. Hirsch, and T. P. Zanos, "Development and validation of a clinical wearable deep learning based continuous inhospital deterioration prediction model," Nature Communications, vol. 16, Art. no. 9513, 2025.
8. G. Huang, X. Chen, and C. Liao, "AI-driven wearable bioelectronics in digital healthcare," Biosensors, vol. 15, no. 7, Art. no. 410, 2025.
9. S. Baumann, R. T. Stone, and E. Abdelall, "Smart healthcare at home: A review of AI-enabled wearables and diagnostics through the lens of the Pi-CON methodology," Sensors, vol. 25, no. 19, Art. no. 6067, 2025.
10. H. Khan, R. Kavati, S. S. Pulkaram, and A. Jalooli, "End-to-end privacy-aware federated learning for wearable health devices via encrypted aggregation in programmable networks," Sensors, vol. 25, no. 22, Art. no. 7023, 2025.
11. B. Almogadwy and A. Alqarafi, "Fused federated learning framework for secure and decentralized patient monitoring in healthcare 5.0 using IoMT," Scientific Reports, vol. 15, Art. no. 24263, 2025.
12. N. Alharbe and M. Almalki, "IoT-enabled healthcare transformation leveraging deep learning for advanced patient monitoring and diagnosis," Multimedia Tools and Applications, vol. 84, pp. 21331–21344, 2025.
13. A. Sameh, M. Rostami, M. Oussalah, R. Korpelainen, et al., "Digital phenotypes and digital biomarkers for health and diseases: A systematic review of machine learning approaches utilizing passive non-invasive signals collected via wearable devices and smartphones," Artificial Intelligence Review, vol. 58, Art. no. 66, 2025.
14. R. A. Fraser, R. J. Walker, J. A. Campbell, O. Ekwunife, et al., "Integration of artificial intelligence and wearable technology in the management of diabetes and prediabetes," npj Digital Medicine, vol. 8, Art. no. 687, 2025.
15. J. Phipps, B. Passage, K. Sel, J. Martinez, M. Saadat, et al., "Early adverse physiological event detection using commercial wearables: Challenges and opportunities," npj Digital Medicine, vol. 7, Art. no. 136, 2024.

16. K. Mahato, T. Saha, S. Ding, S. S. Sandhu, A.-Y. Chang, et al., "Hybrid multimodal wearable sensors for comprehensive health monitoring," Nature Electronics, vol. 7, pp. 735–750, 2024.
17. C. V. F. Pereira, E. M. de Oliveira, and A. D. de Souza, "Machine learning applied to edge computing and wearable devices for healthcare: Systematic mapping of the literature," Sensors, vol. 24, no. 19, Art. no. 6322, 2024.
18. H. S. Saad, J. F. W. Zaki, and M. M. Abdelsalam, "Employing of machine learning and wearable devices in healthcare system: Tasks and challenges," Neural Computing and Applications, vol. 36, pp. 17829–17849, 2024.
19. P. Daniore, V. Nittas, C. Haag, J. Bernard, R. Gonzenbach, et al., "From wearable sensor data to digital biomarker development: Ten lessons learned and a framework proposal," npj Digital Medicine, vol. 7, Art. no. 161, 2024.
20. H. Yuan, S. Chan, A. P. Creagh, C. Tong, A. Acquah, et al., "Self-supervised learning for human activity recognition using 700,000 person-days of wearable data," npj Digital Medicine, vol. 7, Art. no. 91, 2024.